Field hyperspectral imagery as a tool for plant monitoring: application to wheat nitrogen content

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Abstract

In the study presented here, we used a pushbroom CCD camera fitted on a motorised tractor rail to take hyperspectral images of wheat plots. Reflectance correction was performed using a ceramic plate as a reference.
The hyperspectral images have been used to build nitrogen (N) content images for wheat plots using two Partial Least Square regression models. The first chemometrical model was calibrated on nitrogen contents (in percentage of dry matter, % DM) obtained in laboratory and flat leaf normalised spectra (5 latent variables, R^2 = 0.907, RMSEP = 0.326 N % DM); the second one on greenhouse pot plant leaf spectra (8 latent variables, R^2 = 0.919, RMSEP = 0.412 N % DM). Subsequently, they were directly applied to field plant spectra, providing images of nitrogen content. The range of nitrogen content values in these images was not satisfactory. Due to important spectral differences between greenhouse pot plant leaf spectra and field leaf spectra, a model calibrated directly on field leaves is necessary.

Keywords
Close-range hyperspectral images, reflectance, chemometrical model, nitrogen content, wheat

1. Introduction

Vegetation monitoring is a major issue for agriculture, crop genetical selection, etc. Nitrogen content, water status, can be obtained by destructive laboratory measurements. However, non-destructive measurement methods are needed to follow a same plant over time. One of them is the use of spectroscopic measurement. Light hitting a leaf is partially reflected depending on optical properties of leaf constituents. Studying the reflected signal can give information about leaf physiological status (Curran (1989)).
In agronomy, vegetation reflectance spectra are largely used and make agronomical data acquisition possible at plant or leaf scale. A large amount of wavelengths generating a continuous spectrum provides us with accurate information even though partially redundant.
Spectroscopy, formerly reserved to laboratory samples has been extended to field spectroscopy from the fifties (Milton et al. (2009)) and has been generalised over the last years thanks to the development of robust field spectroscopy devices (Milton et al. (2009)). Different devices can be used to collect spectra on an organ like a leaf or on a whole plant. Spectral measurements are used to obtain information about leaf area (Baret et al. (1987)) or chlorophyll concentration (Hansen and Schjoerring (2003)), and to assess total dry matter (Aparicio et al. (2002)).
At another scale, many hyperspectral airborne or satellite sensors have been developed these last years (Casi, Hyperion, Hymap, Aviris…). Hyperspectral imagery can help to assess within-field yield variability thanks to vegetation indices (Zarco-Tejada et al. (2005)) or chlorophyll content by combining an indice-based approach and a radiative transfer model inversion (Haboudane et al. (2002)). (Inoue (2003)) reviewed different ways of combining methods to access agronomic data from remote sensing.
Due to their elevation, satellite or airborne sensors have a wide swath and are well-suited to studies on a large area. Unfortunately, due to their poor spatial resolution, they conduct to mixed pixels and to difficulties to estimate quantitatively and very accurately agronomical parameters

like nitrogen content. At the contrary field spectroscopy can provide “pure” spectra, i.e. concerning vegetation only, but for a smaller area and with a lesser representativeness of the study area.
Sometimes, it is required to have both pure spectra and good area representativeness. It is the case for crop genetical selection for example. Geneticists need accurate estimation of agronomical parameters for a small homogeneous area (micro-plot). A new technology can be tested for this kind of study: close-range hyperspectral sensing. Its representativeness is good because it provides an image of the whole plot. However, it provides pure spectra because spatial resolution is very high. The study presented here evaluates the potential of such a technology to obtain agronomical information on wheat.
The aim of this article was to study the feasibility and the difficulties involved in using of ground hyperspectral imagery for crop characterisation. For that purpose, several chemometrical models between reflectance spectra and leaf nitrogen content were build. Subsequently, their application was tested on field images of durum wheat in order to see whether leaf nitrogen content could be predicted at several phenological stages.

2. Material and method

2.1. Hyperspectral image acquisition system

All hyperspectral images were acquired with a pushbroom CCD camera (HySpex VNIR 1600 - 160, Norsk Elektro Optikk, Norway) fitted on a tractor-mounted motorised rail (see Figure 1). The camera spectral range was from 400 nm to 1000 nm divided in 160 bands (3.7 nm spectral resolution). The first image spatial dimension was determined by the 1600 across-track pixels of the CCD matrix and the second one came from the camera forward movement on the ramp. At 1 m above the vegetation and with a nadir sighting, the ground track was about 30 cm and the spatial resolution across track was 0.2 mm (the lens and the view angle were fixed). The spatial resolution along track was set to 0.5 mm. The integration time, i.e. the time duration during which sensor is storing light energy was fixed manually by the user depending on meteorological conditions (cloudy or sunny weather).

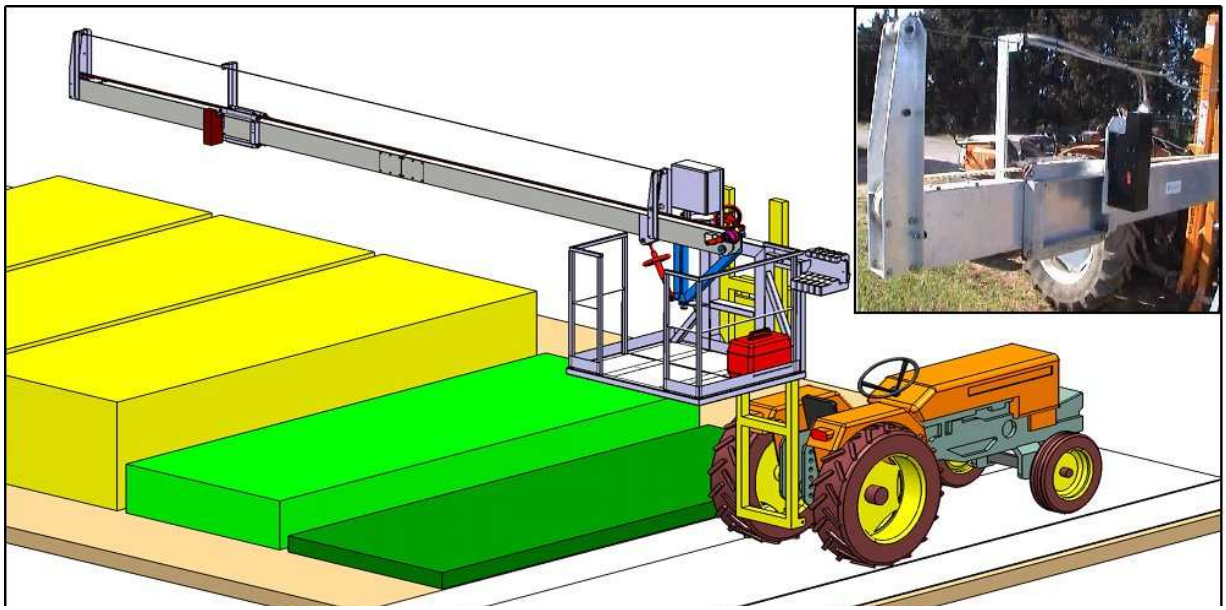

Figure 1: Prototype developed by Cemagref.

2.2. Reflectance correction

Images were first corrected in radiance using sensor characteristics (e.g. spectral sensitivity) provided by the manufacturer. Radiance is the product of the target reflectance, which is intrinsic information and the illumination during image acquisition, i.e. in our case solar lighting.

$$L = R \cdot E \quad \textbf{(1)}$$

Radiance can not be used directly because illumination depends on date and meteorological conditions. To obtain the variable of interest R, it is thus necessary to know the illumination. For that purpose, spectralon® (Labsphere, Inc., New Hampshire, USA) placed in the field of view of the sensor is commonly used because it is a perfect Lambertian diffuser. Another alternative is to use a reference whose spectral characteristics are known.
Indeed, in given lighting conditions:

$$L_{target} = R_{target} \cdot E \quad \textbf{(2)}$$

$$L_{ref} = R_{ref} \cdot E \quad \textbf{(3)}$$

$$R_{target} = \frac{L_{target}}{L_{ref}} \cdot R_{ref} \quad \textbf{(4)}$$

where *R* designs the reflectance, *L* the radiance, and *ref* the reference.
In this study, we used a ceramic plate appropriate for an every day field use. R_{ref} was obtained from laboratory measurements.

2.3. Experimental protocol

2.3.1. Flat leaves

During the 2009 growing season, many wheat leaves of four genotypes (ixos, primadur, neodur and lloyd) were cut, oven-dried and conserved in a cold room. Dried wheat leaves were then flat imaged (see Figure 2). In order to have an homogeneous background, we used the leaf-clip disc of a field spectrometer (FieldSpec®, Analytical Spectral Devices, Inc. (ASD), Boulder, Colorado, USA) designed to be totally black. Leaf nitrogen content was measured in laboratory (Dumas method). Hyperspectral images were corrected in reflectance. Then, a mean reflectance spectrum was calculated for each leaf. Thus we had for each leaf a reflectance spectrum and an actual nitrogen content value. The dataset contained 146 couples spectrum/nitrogen content. The nitrogen content range was 0.40 – 3.78 N % DM.

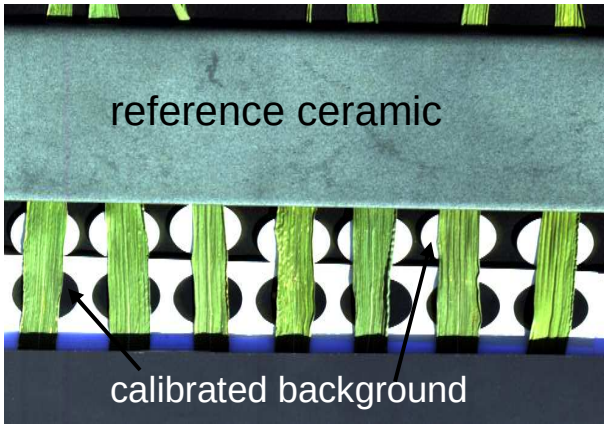

Figure 2: Experimental protocol: flat leaves

2.3.2.Standing plants

In winter 2009 - 2010, some plants were grown in greenhouse with two nitrogen treatments: with or without nitrogen supply. Four genotypes (lloyd, neodur, primadur and ixos) were imaged at five phenological stages (tillering, 2 nodes, flowering, 450 degree days after flowering and maturity) with three repetitions. For each image, two genotypes and three repetitions at one stage were imaged in order to have several pots in the same image and thus to try to simulate field conditions (see Figure 3). On each plant the two upper leaves were marked with coloured plastic collar and thereby located on the images. After each image acquisition, leaves were cut and sent to the laboratory for destructive nitrogen content measurement. For each image, we drew regions of interest on marked leaves and obtained therefore their mean reflectance spectrum. Consequently, we had for each plant two couples (one for each of the two cut leaves) leaf reflectance spectrum / actual nitrogen content. The dataset contained 180 couples spectrum/nitrogen content. The nitrogen content range was 0.81 – 5.52 N % DM.

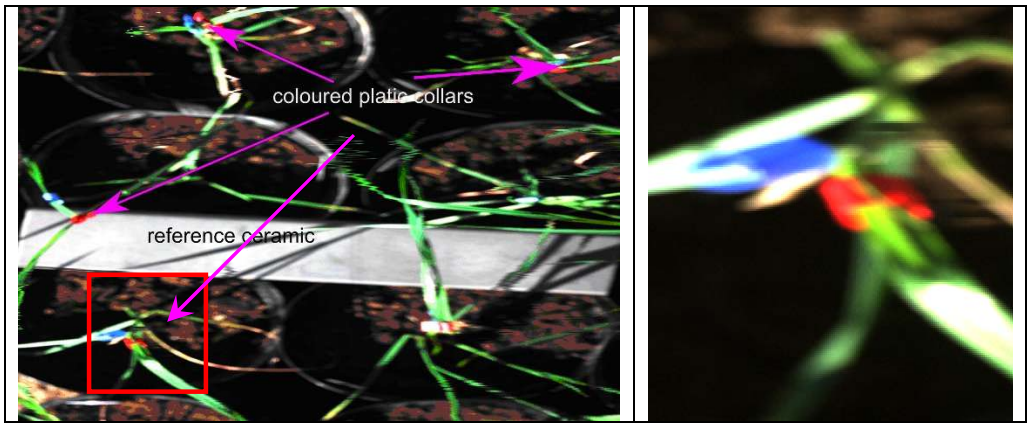

Figure 3: Experimental protocol: standing plants

2.3.3. Field images

During the whole growing season, several micro-plots were imaged at six key phenological stages: 3 leaves (24/02/2009), tillering (10/03/2009), 1-cm ear (06/04/2009), stem elongation (10/04/2009), heading (30/04/2009), and maturity (12/06/2009).

2.4. Chemometrical model calibration

As we will see below, several models were calibrated, using either flat leaf data (cf. § 2.3.1) or standing plant leaf data (cf. § 2.3.2). Model calibrations were computed with partial least square regression (PLS) using Matlab software (TheMathWorks, Natick, MA, USA) and our own functions. For each experiment, we split the dataset in a calibration set of two third of the samples and a test set of one third of the samples, having both the same distribution. We calibrated the model by cross-validation leave-one-out on the calibration set. The best calibration equation was selected on the basis of a large coefficient of multiple determinations (R^2) and a low standard error of cross-validation (SECV). SECV is a measure of the difference between the actual and predicted values calculated over all cross-validation calibrations. Next the model was tested on the independent test set.

3. Results and discussion

3.1. Reflectance correction

Reflectance theoretically depends on both illumination and viewing configurations, this phenomenon being formalised by a bidirectional reflectance distribution function (BRDF). However, to a first approximation, a leaf can be considered as a Lambertian surface (Chelle (2006); Grant (1987)), i.e. its BRDF is a constant. So flat leaves and inclinated leaves have the same reflectance at a nadir viewing. Nevertheless, due to their dissimilar orientation toward the sun, all leaves do not receive the same level of illumination. They do not receive either the same level than the reference ceramic. Each illumination level is linked to the cosine of the angle between the surface and the light incidence. Because this difference is independent of the wavelength, it can be introduced as a multiplicative factor.
The reflectance for field leaves obtained with the correction described above (see § 2.2) is thus their actual reflectance up to a scalar factor. Such a multiplicative effect can be removed by spectrum normalisation. Therefore, in order to be applied on field leaves, model must use normalised spectra.

3.2. Flat leaf model

3.2.1. Model prediction quality

On Figure 4, we can see the results of calibration and test steps. The best model was obtained for normalised spectra and with 5 latent variables (LV). Model was considered as satisfactory even if error seems to slightly increase with nitrogen content.

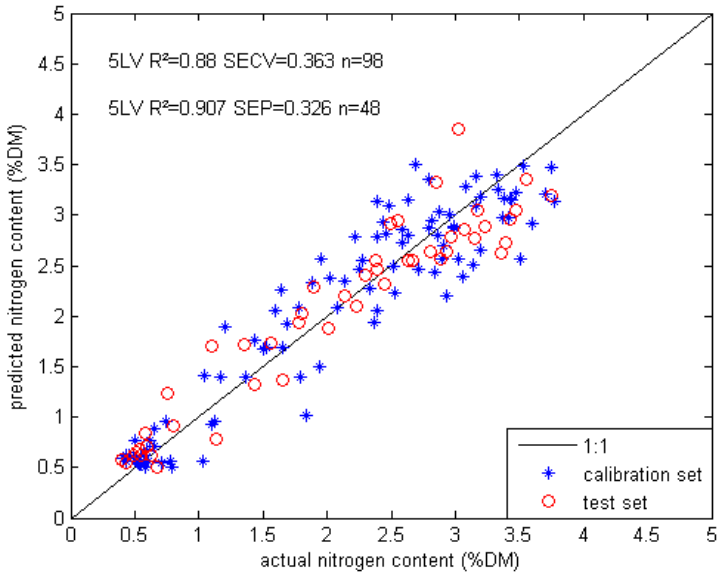

Figure 4: Prediction quality of flat leaf chemometrical model for calibration set (blue stars) and test set (red circle). SEP means standard error of prediction.

3.2.2. Application to field images

The model was applied on field images. Figure 5 presents the results for the genotype primadur at the stem elongation stage. NDVI (Normalised Difference Vegetation Index (Tucker (1979))) was computed on the hyperspectral image. A mask was created by thresholding this NDVI value and was applied on image to select vegetation pixels.

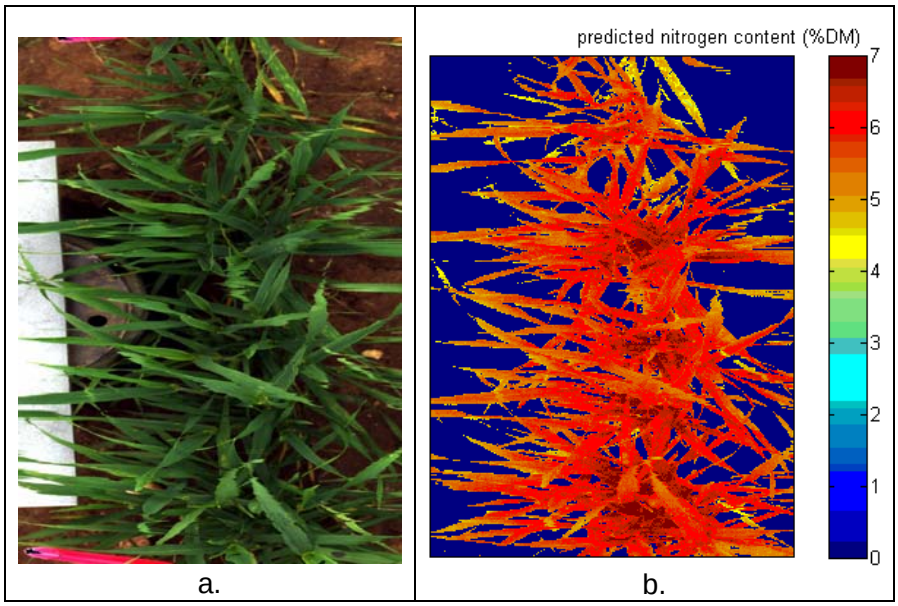

Figure 5: a. Colour image of plot at stem elongation stage (ceramic reference is visible on the left), b. Cartography of predicted nitrogen content obtained with the model calibrated on flat leaves.

Although we do not have ground truth for each pixel of the image, the model seems to overestimate the nitrogen content on field leaves, which is not in agreement with expert expectations. Moreover, in April (at stem elongation), nitrogen content obtained by other measurements (leaf-clip spectrometer for example) is around 3.5 – 4 %. We can put forth some hypotheses to explain that. Firstly, the model has been calibrated on dried leaves. Normally water content does not influence reflectance spectra in the 400 – 900 nm spectral range but drying leaves can generate polyphenols, disrupting model calibration. Secondly, the model was calibrated on flat leaves and did not take into account field scene effects like specular or multiple reflexions. That is why we decided to calibrate a model directly on leaves on standing plants. For practical reasons (notably growing season was ended), the new model was calibrated on leaves of plants grown in pots in a greenhouse.

3.3.Standing plant leaf model

3.3.1.Model prediction quality

On Figure 6, we can see the results of calibration and test steps. The best model was obtained for normalised spectra and with 8 latent variables. The model is not totally satisfactory because the set contains three big groups and not a continuous range. Nevertheless this figure shows that it is possible to calibrate a model directly on standing plant leaves.

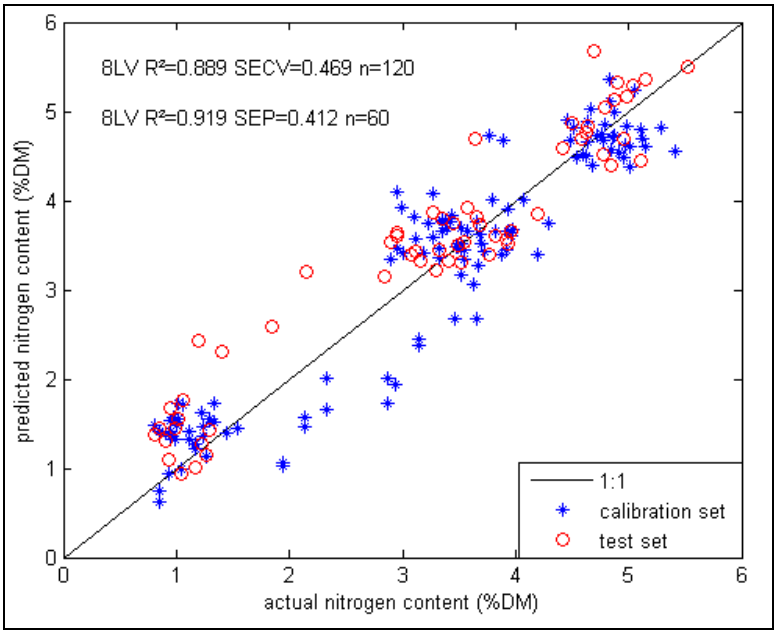

Figure 6: Prediction quality of standing leaf chemometrical model for calibration set (blue stars) and test set (red circle). SEP means standard error of prediction.

3.3.2.Application to field images

In order to see if a model calibrated on leaf of standing plant (and thus taking into account field scene effects) was better than a model calibrated on flat leaves, we applied this new model on field images. Once again, nitrogen content for leaf was overestimated (see Figure 7).

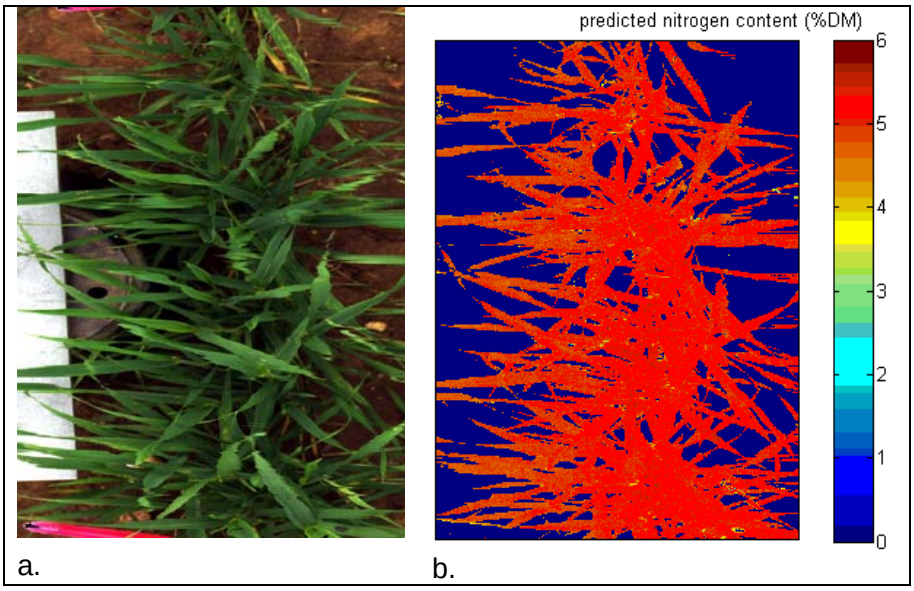

Figure 7: a. Colour image of plot at stem elongation stage (ceramic reference is visible on the left), b. Cartography of predicted nitrogen content obtained with the model calibrated on standing plants.

An in-depth study of the model coefficients showed that the model was calibrated principally on the visible domain and on the ratio between visible and near infra-red domains. Figure 8 shows that these spectral characteristics are precisely the ones where greenhouse standing plant leaves spectra and field leaves spectra differ. That is why model calibrated on standing plant leaves do not give good results with field leaves.

This difference can probably be explained biologically. Plants in greenhouse grow faster than field plants and often the plants are delicate and their leaves are thinner, that could lead to these differences in the reflectance spectra.

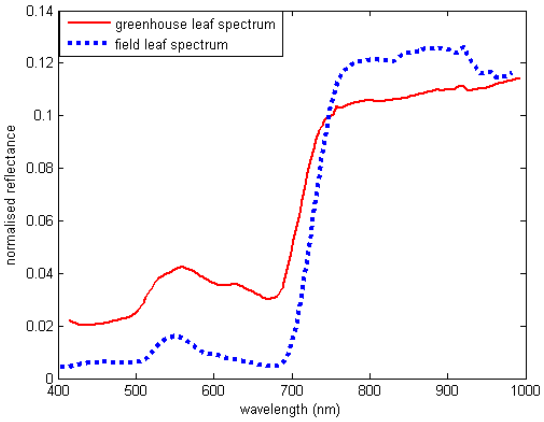

Figure 8: Normalised spectra comparison between field leaf spectrum (blue dash) and greenhouse leaf spectrum (solid red).

4.Conclusion

In this article, we studied a new kind of hyperspectral technology: a close-range field imaging system. We took images at 1 m above the canopy of wheat plots. We used a ceramic plate as a reference to correct images in reflectance, conducting to a reflectance up to a scalar factor for inclinated leaves.
We calibrated chemometrical models on flat isolated leaves and on pot plant leaves. These experiments demonstrated that it is possible to calibrate a chemometrical model between reflectance spectra and nitrogen content with a close-range imagery system and that it could be applied to various genotypes. However, it has been shown that a model calibrated on flat leaves or even on standing greenhouse plant leaves can not be applied directly to field leaves.
As a conclusion, close-range hyperspectral imagery still seems a suitable tool for nitrogen content monitoring of field leaves, but it requires imperatively that the model is calibrated on field leaves also. The next step will be to acquire such a calibration data set.

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